QUALITY-BASED DYNAMIC THRESHOLD FOR IRIS MATCHING

Wenbo Dong, Zhenan Sun, Tieniu Tan, Zhuoshi Wei
Center for Biometrics and Security Research
National Laboratory of Pattern Recognition
Institute of Automation, Chinese Academy of Sciences
{wbdong, znsun, tnt, zswei}@nlpr.ia.ac.cn

ABSTRACT

Current iris recognition systems usually regard poor quality iris images useless since defocused or partially occluded iris images may cause false acceptance. However, such a strategy may lose an opportunity to correctly report a genuine match with poor-quality samples. This paper proposes an adaptive iris matching method to improve the throughput of iris recognition systems. The core idea of the method is to dynamically adjust the decision threshold of iris matching module based on the quality measure of input iris image. So that the poor quality iris images also have a chance to match template database under the controlled false accept rate. Experiment results on the real system demonstrate the effectiveness of the proposed method and the recognition time is expected to be greatly reduced.

Index Terms— Iris recognition, iris matching, image quality assessment, dynamic threshold, iris image acquisition

1. INTRODUCTION

Iris recognition has become an important technology in high-security applications because of its high accuracy and robustness **[1][2]**, but iris recognition devices are far from ideal conditions. Iris acquisition systems always have limited capturing range and therefore acquire too many poor-quality iris images, especially when users are at a distance and on the move **[3]**. All poor-quality images can not pass the iris quality assessment and therefore impossible to be recognized. The purpose of this paper is just to discuss whether we can make use of those poor-quality images, so that they also have a chance to be accepted.

Daugman developed the first integrated iris recognition algorithm. He use Gabor filters to extract iris features and matched two iris codes by the Hamming distance (HD). He also demonstrated that the distribution of hamming distance of different pairs of iris codes fits the binominal distribution, and its randomness can guarantee low false matching rate in billions of iris comparisons **[2]**. Many other researchers put forward new algorithms on iris recognition and their work can be found in literatures such as **[4] [5]** and **[6]**. Their methods of iris feature extraction are different, but most of them use iris matching strategy based on Hamming Distance (HD). The performance of an iris recognition algorithm is evaluated by the false accept rate (FAR) and false reject rate (FRR) and most of state-of-the-art algorithms achieve good performance on good-quality iris image databases. However, those algorithms are not practical in the real applications, because it is hard to find the good-quality image in the video sequence and almost all images are regarded poor-quality and discarded. It is the reason why iris recognition device is difficult to use.

In this paper, we propose a method of "quality-based dynamic threshold" for iris matching. We deal with those poor-quality images as well as good ones, but set a dynamic decision threshold based on the image quality. This threshold is set lower for good-quality images and set higher for poor-quality ones. With this strategy, poor-quality images also have an opportunity to be accepted, but it will not increase the FAR, since FAR is controlled by the dynamic threshold.

On the other hand, since more images are used, as long as we recognize one image in a video sequence, the recognition is successful. Therefore the throughput of a video sequence is improved, although the FRR of the single image may increase. Experiment results show that our strategy can dramatically increase the accept rate of an iris image sequence in real iris recognition systems.

The rest of the paper is organized as follow. Section 2 briefly introduces our strategy on quality-based dynamic threshold. Section 3 presents our measure to estimate the iris image quality. Section 4 shows experiments in the real iris sequence and presents how our strategy improves the performance of an iris recognition system.

2. DYNAMIC THRESHOLD FOR IRIS MATCHING BASED ON THE IMAGE QUALITY

Through Daugman's observation, the distribution of HDs from millions of inter-class iris matching forms a perfect binomial distribution. Therefore, the decision threshold can be set based on parameters of binominal distribution according to the demanded FAR, for example, 0.35 is set for 1 failure in 10^5 matches, 0.33 for 1 in 10^6 millions, and 0.30 for 1 in 10^9. It is the reason why iris recognition has low false accept rate and more accurate than other biometrics, such as face recognition and fingerprint recognition **[2]**.

From our experience, the binominal distribution of inter-class iris matching is not invariable, but changes with the image quality of the iris database. For good-quality images, the variance of the distribution is small, while for poor-quality ones, the variance of the distribution is large. Figure 1 shows two HD distributions in two different databases. The solid curve is the HD distribution of in a good-quality database 1. The dashed curve is the distribution in a poor-quality database 2.

Obviously, we should not deal with these two databases by the same method. If we use t_1 as the decision threshold in both two databases, the FAR in database 2 will increase, while if we use t_2 in both two databases, the FRR in database 1 will increase. So we set the variable decision threshold as t_1 for database 1 and t_2 for database 2. Then the dilemma is solved and that is so-called dynamic threshold. This threshold is relevant with the image quality.

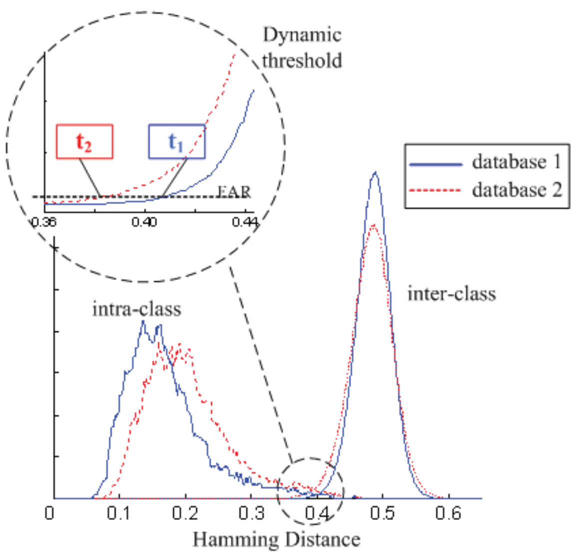

Fig. 1 Dynamic threshold for different databases

2.1. Inter-class HD distributions in iris databases with different image quality

We use CASIA 1.0 **[7]** as the original iris database and define its name as Q1 database. Then we establish several synthetic poor-quality databases by smoothing images of Q1 with different-scale Gaussian kernels. We named these databases as database Q2, Q3 and Q4 to represent the different degree of image blurring (Quality of Q2 is better than Q3 and Q3 is better than Q4).

All possible inter-class iris matching on these databases is performed, and Figure 2 (a) shows those distribution curves. The curve Q1-Q1 is inter-class comparisons in database Q1, the curve Q1-Q2 is inter-class comparisons between Q1 and Q2, and so on. We can see that the standard deviation of the inter-class distribution decreases with the iris image quality.

We also set up synthetic iris databases by down-sampling images in Q1 database. Database R1 is down-sampled by $1/\sqrt{2}$ from iris images in Q1, database R2 is down-sampled by $1/\sqrt{3}$, and database R3 is down-sampled by $1/\sqrt{4}$. The inter-class matching results are plotted in the Figure 2 (b). The standard deviation of distributions between Q1 and R1, R2, R3 also decreases with the iris image scale.

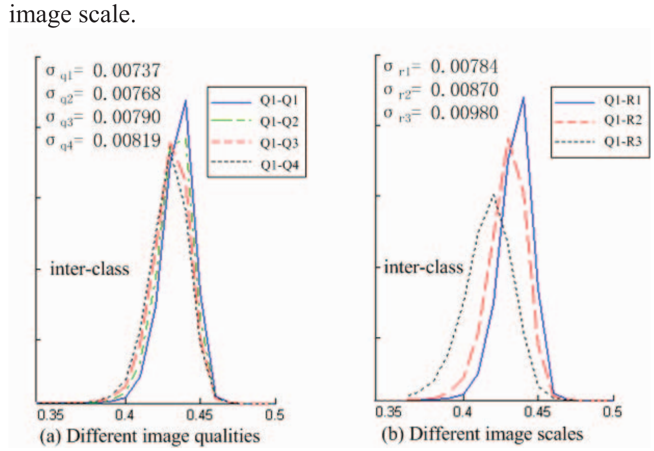

Fig. 2 Inter-class HD distributions in different databases

As a note, the iris localization method and feature extraction method is based on our previous work **[8]** and **[5].** The feature code is 1024 bytes, matched in 9 different rotation angles. Since the iris recognition algorithm is not the focus of this paper, it is not discussed further.

2.2. The relationship between the decision threshold and the image quality

The setting of the dynamic threshold is based on the image quality. We want to know how to describe the relationships between the threshold and the image quality.

Here we still use the model of binominal distribution to represent the distribution of HDs. We define p as the mean and N as the degree-of-freedom of a binominal distribution, so the probability of HD distribution is calculated by (1). **[2]**

$$f(x) = \frac{N!}{m!(N-m)!} p^m (1-p)^{N-m} \tag{1}$$

Where $x = m/N$, presenting the matching score and $f(x)$ is the probability when matching score equals to x. If we want to control FAR to an expected value, then the decision threshold t should be calculated by (2).

$$t = p - f^{-1}(FAR) \tag{2}$$

If we know the exact p and N when two different qualities of iris images are matched, the dynamic threshold can be directly set by (2). Define the quality of two irises as q_1 and q_2, we expect p and N presented as such a function:

$$(p, N) = g(q_1, q_2) \tag{3}$$

Unfortunately, this function g is hard to be explicitly represented, since g depends on the feature extraction method, the quality measure and many other factors. It is too complicated to study this relationship.

While, we still have other methods to implicitly present this function, for example a look-up table. For every iris databases with different image quality, we calculate their average quality value. Then from the experiments of inter-class iris matching, we can statistically calculate the two parameters p and N of the distribution of each iris database.

$$\begin{cases} p = \frac{1}{n}\sum_{i=0}^{n} HD_i \\ \sigma^2 = \frac{1}{n}\sum_{i=0}^{n}\left(HD_i - p\right)^2,\ N = p\left(1-p\right)/\sigma^2 \end{cases} \quad (4)$$

Finally a look-up table like Table 1 is gotten. From such tables, we can easily find the corresponding relationship between (p, N) and the quality of two iris images. Then we can use (2) to calculate the needed decision threshold. The real look-up table is much larger than Table 1 and saved in the computer memories.

Table 1 Quality-based dynamic threshold with the expected false accept rate

Quality of 2 images	mean p	Degree N	Expected FAR		
			1 in 10^5	1 in 10^6	1 in 10^9
Q1-Q1	0.430	4514	0.337	0.324	0.304
Q1-Q2	0.429	4261	0.333	0.321	0.291
Q1-Q3	0.428	3925	0.328	0.316	0.284
Q1-Q4	0.426	3648	0.323	0.310	0.278
Q1-R1	0.428	3983	0.330	0.317	0.286
Q1-R2	0.424	3228	0.313	0.300	0.267
Q1-R3	0.420	2533	0.297	0.281	0.242

3. QUALITY MEASURE

There are many measures to evaluate the iris image quality, such as defocus, motion-blur, occlusion, dilation and so on **[9]**. For out-of-focus image, Daugman uses an 8×8 operator **[2]** to analysis the high frequency component of iris images, and Wei et al. **[10]** also use a similar 5×5 operator, while Ma et al. **[4]** add another dimension with the ratio between the high-frequency and the medium-frequency components to calculate the focus value. Jain et al. **[11]** uses the wavelet analysis to differentiate clear images from blurred images. Krichen et al. **[12]** divides images into high quality and poor quality by machine learning. Belcher et al. **[13]** uses the informational measure to assess iris image quality. The image quality is finally normalized to a percent value to rank the iris image quality.

We divided such measures into two categories. One is relative to image acquisition, such as defocus and motion-blur, and the other is about occlusion of eyelid and complexity of iris texture, which represents intrinsic characters of iris and does not change itself.

For the former, we firstly calculate the focus value F1 based on Daugman's the 8×8 operator, and then rescale the image to half size and calculate the focus value F2. F1 and F2 respectively represent the high-frequency and medium-frequency components, and *F1/F2* is the ratio between them, which is robust against texture complexity and illumination changes. Then we define the measure as M_1

$$M_1 = \begin{cases} 0, & F1 + F2 < \tau \\ (\alpha F1 + \beta F2 + \gamma \frac{F1}{F2}) \cdot 100\% & \end{cases} \quad (5)$$

Where, α, β, γ and τ are parameters for weighting, which are obtained by experiences and learning.

For the later, another measure M_2 is calculated by combining the pixel number of iris's diameter P, occlusion ratio O and dilation ratio D. M_2 is calculated in the iris region after the iris segmentation is finished.

$$M_2 = \left(\frac{P}{P\max}\right)^2 \cdot O \cdot D \cdot 100\% \quad (6)$$

We use $M_1 \bullet M_2$ as quality measures to assess an iris image and the image quality value is ranked from 0 to 100.

4. EXPERIMENTS ON REAL IRIS SEQUENCE

In Section 2, we have introduced our method of quality-based dynamic threshold for iris matching. In this section, we will show how it improves the performance of the real iris recognition systems.

4.1. Iris image acquisition and database establishment

A camera of 4 mega pixels is used to acquire iris sequences at speed of 15 frames per second. Eye images are cut from high-resolution images when eyes are detected and the image quality are not very bad. The database totally includes 150 candidates, and each has 60 eye images.

We divided these images into 10 different databases according to the above image quality value. The images with quality of 90 to 100 made up of database DB10, and the images with quality of 80 to 90 made up of database DB9, and so on. Since images in DB to DB3 are too bad, only DB4 to DB10 are investigated.

4.2. Improve the performance of the system

DB10 is considered as the registration database and we make inter-class comparisons between irises in DB10 and other databases, and then create the look-up table of dynamic threshold like Table 1. Then we make intra-class comparisons between irises in DB10 and other databases, and make decision by the dynamic threshold in the table.

Figure 3 shows how the proposed method improves the system performance. In traditional methods, iris images are divided into good images and "should-be-discarded" images. The latter have no chance to be accepted, since they may bring the increase of FAR. But with our method, all images can be used and poor-quality images also have a chance to be accepted based on the dynamic decision threshold.

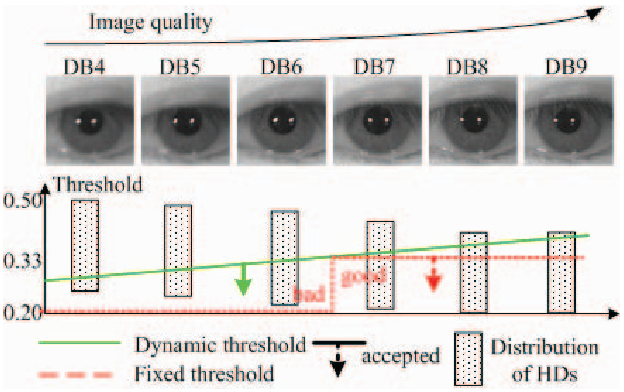

Fig.3 Improvement of accept rate with dynamic threshold

Table 2 gives parts of experiment results. F-TH1 set the quality cut-line as 60 as in Fig. 3, so images in DB4, DB5 and DB6 is cut off, and other images in DB7, DB8 and DB9 all use the decision threshold of DB7 for ensuring FAR=10^{-6}. Similarly, F-TH2 set the cut-line as 50 and F-TH3 set the cut-line in 40. Their accept rates are all worse than dynamic threshold (D-TH). But with our strategy, every image can be used, and the quality-based dynamic decision threshold ensures FAR. As a result, our strategy achieves the best performance in those databases. It is expected to greatly improve the throughput of genuine report times in the real iris image sequence.

Table 2 Accept rate with dynamic threshold (D-TH) and with fixed threshold (F-TH) when FAR = 10^{-6}

	DB4	**DB5**	**DB6**	**DB7**	**DB8**	**DB9**
F-TH1	**0**	**0**	**0**	**76%**	81%	91%
F-TH2	**0**	**0**	**68%**	72%	78%	89%
F-TH3	**0**	**41%**	61%	65%	72%	78%
D-TH	**22%**	**41%**	**68%**	**76%**	**84%**	**94%**

4.3. Discussion and comments

- Since more images in the video sequence are used, as long as we recognize one of them, the recognition is successful. Therefore the throughput of the whole video sequence is improved. Although FRR of the single image may increase, it does not matter.
- The mentioned database consists of all kinds of images captured in the real circumstance, so although we do not make experiments on real systems, the result can prove our method effective on the real image sequence.
- Our method may increases the computational cost, but it is not a big problem for state-of-the-art algorithms.

5. CONCLUSION

In this paper, we proposed a method of dynamic threshold for iris matching based on the quality of iris images, so that the poor quality iris images also have a chance to be matched without increasing FAR. Experiments on the real system show that more iris images in video sequence are right accepted. This method is expected to dramatically improved the speed and efficiency of iris systems.

ACKNOWLEDGEMENT

This work is funded by National Basic Research Program (Grant No. 2004CB318100), National Natural Science Foundation of China (Grant No. 60736018, 60702024, 60723005), and National Hi-Tech R&D Program (Grant No. 2006AA01Z193, 2007AA01Z162).

11. REFERENCES

[1] J. Daugman, "Probing the uniqueness and randomness of iriscodes: results from 200 billion iris pair comparsions", Proc. of IEEE, vol. 94, pp.1927-1935, 2006

[2] J. Daugman, "How iris recognition works", IEEE Trans. Circuits Syst. Video Technol., vol. 14, pp. 21-30, 2004

[3] J. R. Matey, O. Naroditsky, K. Hanna, etc., "Iris on the move: acquisition of images for iris recognition in less constrained environments", Proc. of IEEE, vol.94, pp. 1936-1947, 2006

[4] L. M, T. Tan, Y. Wang and D. Zhang, "Personal identification based on iris texture analysis", IEEE Trans. Pattern Anal. Mach. Intell., vol. 25, no. 12, 2004

[5] Z. Sun, T. Tan, "Ordinal measures for iris recognition", to appear in IEEE Trans. Pattern Anal. Mach. Intell. 2009

[6] D. Monro, S. Rakshit and D. Zhang, "DCT-based iris recognition", IEEE Trans. Pattern Anal. Mach. Intell. vol. 29, no. 4, pp. 586–595, 2007

[7] CASIA image database, available from: <http://www.cbsr.ia.ac.cn/databases.thm>

[8] Z. He, T. Tan, Z. Sun, X. Qiu, "Towards accurate and fast iris segmentation for iris biometrics", to appear in IEEE Trans. Pattern Anal. Mach. Intell, 2009

[9] Nathan D. Kalka, Jinyu Zuo, Natalia A. Schmid, Bojan Cukic, "Image quality assessment for iris biometric", SPIE Biometric Technology for Human Identification III, pp. 6202:D1–D11,2006

[10] Z. Wei, T. Tan, Z. Sun, J. Cui, "Robust and fast assessment of iris image quality", IEEE Int'l Conf. on Biometrics, pp. 464-471, 2006.

[11] Y. Chen, S.C. Dass, and A.K. Jain, "Localized iris image quality using 2-D wavelets", IEEE Int'l Conf. on Biometrics, pp. 373-381, 2006.

[12] E. Krichen, S. Garcia, and B. Dorizzi, "A new probabilistic iris quality measure for comprehensive noise detection", Biometrics: Theory, Applications, and System, Sept 2007.

[13] C. Belcher, Y. Du, "Feature information based quality Measure for iris recognition", IEEE Trans. Inf. Forensics and Security, vol. 3, no. 3, 2008